

Banking sector concentration risk: consequences and possible prudential implications

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Outline

Introduction & Aims

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Conclusions & Policy implications

Introduction & Aims

Main purpose: measure the degree to which banks are exposed to concentration risk.

Estimate additional capital requirements

Check ex-post whether the risk weights for real sector exposure classes were adequate over a long time frame

Estimate proper (ex post) risk weights to be applied either macro-prudentially (at system level) or at a micro level (bank specific risk weights). However, because RW are fixed, capital buffers can be used for the purpose

Estimate losses incurred by banks due to concentration and compute a concentration capital buffer

Concepts & Literature review (I)

- ✓ There are different approaches quantifying credit risk ranging from single-factor models to complex multi-factor portfolio models.
- ✓ The Asymptotic Single Risk Factor (ASRF) framework of Gordy (2003) is a starting point since this environment underlies the computation the risk-weighted assets (RWA) of the Internal Ratings-Based (IRB) Approach of Basel.
- ✓ Concentration risk can arise from:
 - An unbalanced distribution of exposures to large borrowers: Single name concentrations.
 - Excessive exposure to certain sectors : Sectoral/Segment concentrations.

Concepts & Literature review (II)

Risk concentrations are understood as <u>violations of two specific</u> <u>assumptions</u> of the ASRF model:

✓ The portfolios are highly granular in terms of exposures to individual borrowers

The lower the granularity of the portfolio and the lower number of debtors, the higher the volatility of the observed losses!

✓ Systematic credit risk is fully captured by a single risk factor (not covered by the present study)

Thus, the risk weight shares understate the amount of credit risk in real-life portfolios

Concepts & Literature review (III)

According to Resti (2008) the main differences between the ASRF model and finite-granularity multifactor model are:

- Systemic risk can be represented by just one factor affecting all obligors in the same way, or by many factors, having a different relevance for each single obligor.
- The factor loadings measuring the obligors' vulnerability to the systemic factor is decided by supervisors, or can be measured empirically.
- An infinitely-high number of infinity-small obligors, **versus** a number of obligors with different sizes, including large ones.

Methodology (I) – flow of the research

Data

- On Romania
- December 2017



PD

- PIT
- TTC Calibrated PDs



Losses

- Intermediate loss
- Net loss (non-granular)
- Net loss (granular)

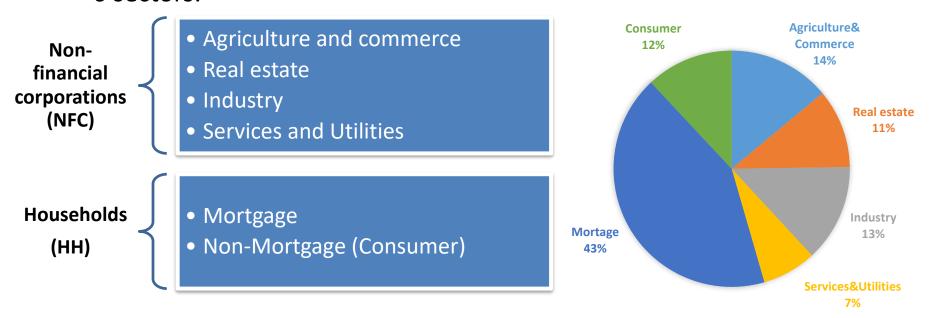


Draws

- 10,000
- Joint default behavior (use of Copulas)

Methodology (II) – data

- Data from The Central Credit Register (CCR) and COREP
- Domestic banking groups and stand-alone banks
- Only performing loans
- 6 sectors:

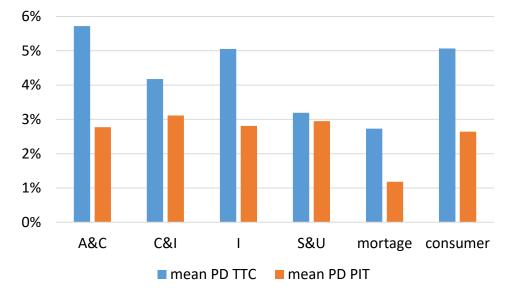


 PIT PDs for each debtor were used based on the output of a rating model previously developed by NBR staff.

Methodology (III) – PD distribution and correlation

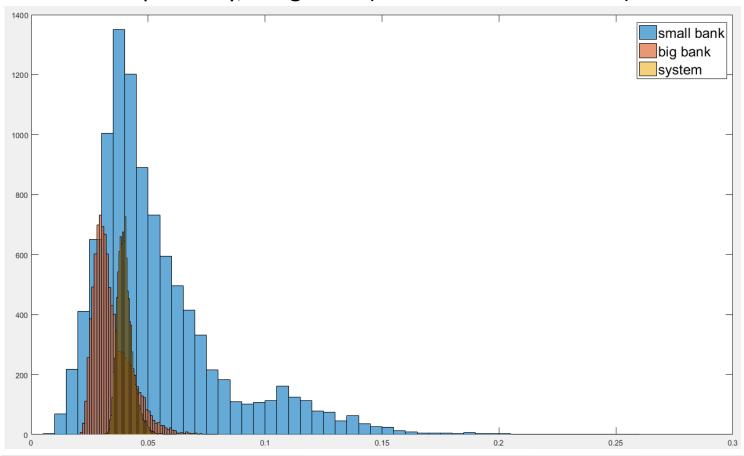
- Long term distributions of default rates were obtained using a nonparametric bootstrap method.
- The point-in-time PDs were calibrated to TTC values to reflect the long behavior (2006-2017).
- Correlations between the 6 sector-specific default rates were used to construct scenarios, using joint distributions of default rates (Gaussian and several Student Copulas). For each type of Copula, 10000 drawings were analyzed.

$$rho = \begin{bmatrix} 1 & 0.84 & 0.74 & 0.69 & 0.66 & 0.68 \\ & 1 & 0.73 & 0.53 & 0.76 & 0.69 \\ & & 1 & 0.62 & 0.73 & 0.64 \\ & & & 1 & 0.38 & 0.47 \\ & & & & 1 & 0.77 \\ & & & & & 1 \end{bmatrix}$$



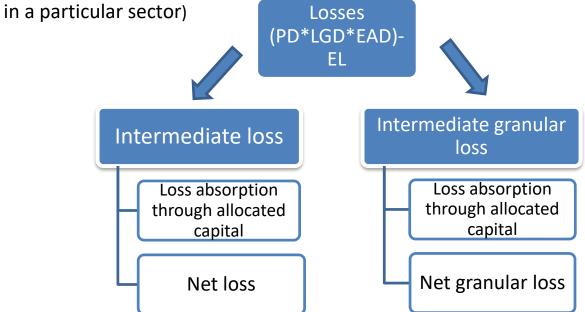
Methodology (III) – PD distribution and correlation

The volatility of the PDs drawn at system level in comparison with the ones from a small bank (under 1% market share) and respectively, a big bank (over 10% market share)



Methodology (IV) – losses computation

- For each drawing, an intermediate loss (loss following the deduction of the EL) and a net loss (deduction of both the EL and allocated capital) were computed. Losses were computed both at the sector level and at portfolio level (both system-wide and for each of the banks).
- Losses were compiled based on:
- ✓ the actual exposures of banks in a particular sector towards different debtors.
- ✓ adjusted exposures, assuming <u>high granularity</u> (each exposure is equal to the average exposure of a bank in a particular sector)



Methodology (V) – data analysis

Concentration for each bank above 1% market share we've computed:

Herfindahl-Hirschman Index

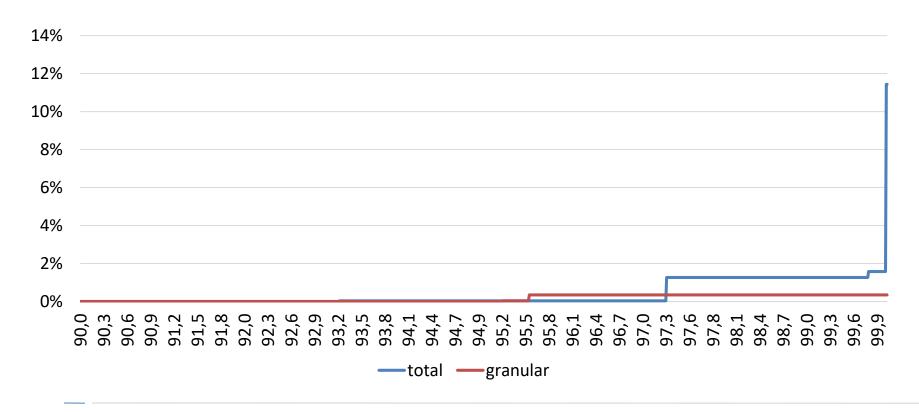
Exposure share on portfolios of each bank

					_1!					
		portfolios								
		Agriculture &Commerc e	Real estate	Industry	Services & Utilities	Mortage	Consumer			
banks	1	0,02	0,06	0,05	0,06	0,00	0,00			
	2	0,03	0,06	0,04	0,05	0,00	0,00			
	3	0,05	0,08	0,08	0,14	0,00	0,00			
	4	0,01	0,05	0,03	0,07	0,00	0,00			
	5	0,04	0,13	0,12	0,25	0,00	0,00			
	6	0,00	0,01	0,01	0,01	0,00	0,00			
	7	0,06	0,09	0,43	0,07	0,00	0,01			
	8	0,01	0,04	0,03	0,08	0,00	0,00	S		
	9	0,09	0,15	0,07	0,15	0,00	0,00	banks		
	10	0,01	0,04	0,09	0,06	0,00	0,00	Q		
	11	0,00	0,01	0,03	0,01	0,08	0,00			
	12	0,01	0,01	0,03	0,07	0,01	0,01			
	13	0,08	0,11	0,16	0,61	0,00	0,02			
	14	0,01	0,05	0,04	0,05	0,00	0,00			
	15	0,02	0,03	0,05	0,07	0,00	0,00			
	16	0,01	0,06	0,03	0,03	0,00	0,00			
	17	0,01	0,13	0,01	0,10	0,00	0,03			

		portfolios					
		Agriculture &Commerc e	Real estate	Industry	Services& Utilities	Mortage	Consumer
	1	3,3%	13,2%	2,7%	5,4%	7,0%	2,0%
	2	8,3%	9,0%	18,3%	13,4%	19,3%	15,8%
	3	2,3%	2,2%	2,3%	2,4%	2,4%	4,5%
	4	6,7%	6,4%	7,0%	12,5%	17,9%	21,0%
	5	0,5%	0,6%	0,7%	0,8%	4,0%	2,1%
	6	17,0%	15,5%	13,7%	13,9%	16,5%	14,4%
	7	0,7%	0,4%	0,9%	0,4%	0,7%	0,2%
S	8	8,0%	8,8%	7,9%	6,9%	6,0%	3,2%
banks	9	1,8%	0,3%	4,7%	1,7%	0,0%	0,0%
ā	10	2,2%	4,2%	3,2%	3,1%	3,3%	3,0%
	11	0,6%	0,6%	0,2%	1,3%	0,0%	2,3%
	12	2,2%	5,6%	0,6%	1,5%	0,1%	0,1%
	13	0,3%	0,7%	0,2%	0,3%	0,4%	0,1%
	14	1,1%	0,6%	0,7%	0,6%	0,2%	0,6%
	15	2,4%	2,5%	1,5%	1,5%	1,3%	1,8%
	16	11,3%	8,3%	6,9%	11,9%	7,4%	22,2%
	17	20,1%	13,3%	21,6%	13,8%	6,5%	1,4%

Results (I)*

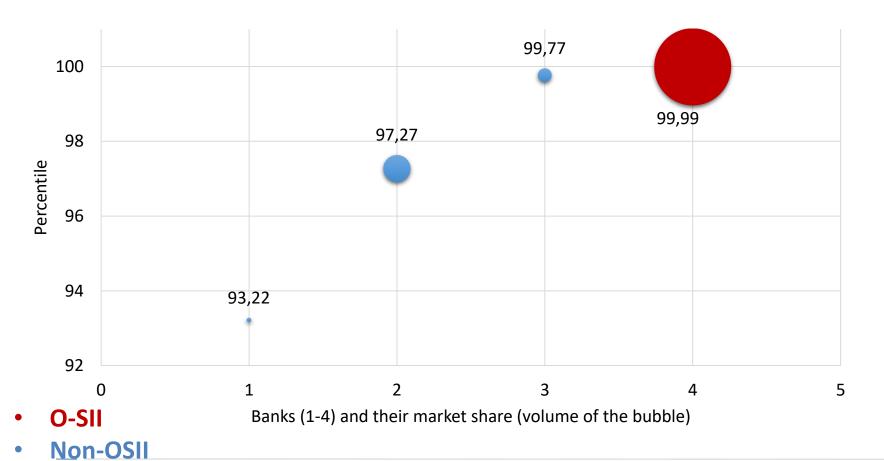
 The cumulative market share of banks that record losses at overall portfolio level for different percentiles of the loss distributions





Results (II)

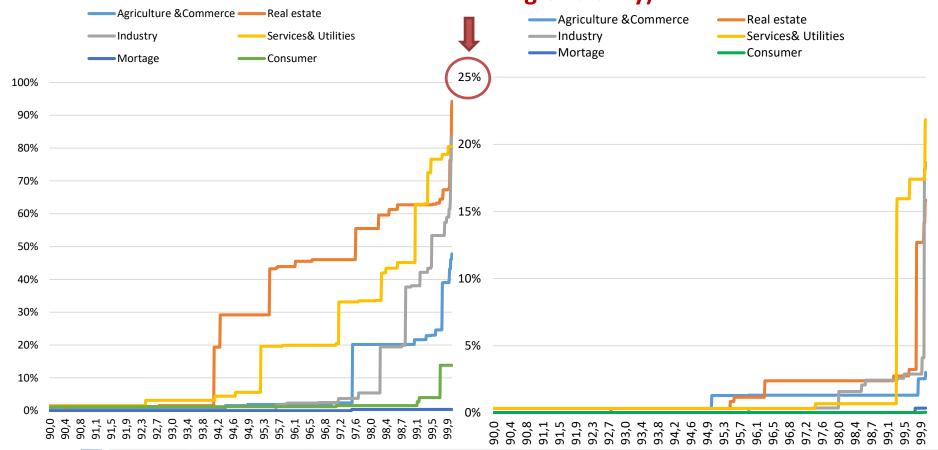
 The range of the loss distribution percentile against the market share of banks with simulated net losses at aggregate portfolio level



Results (III)

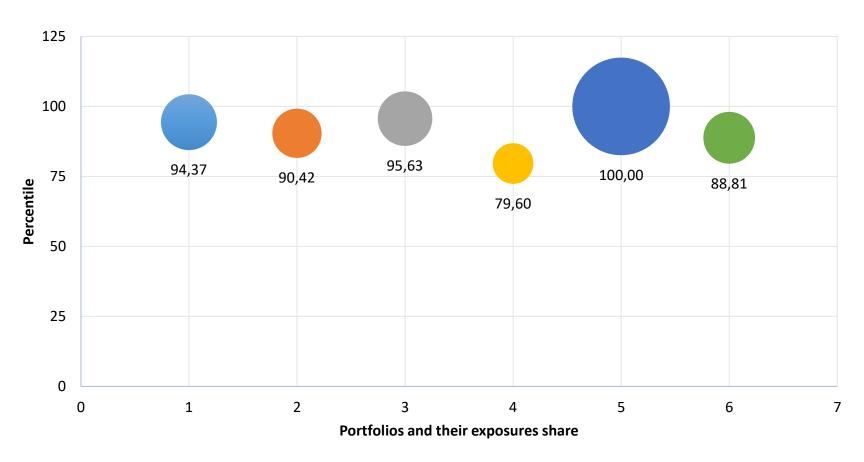
The cumulative market share of banks
 that record losses on <u>each</u> portfolio

The cumulative market share of banks that record losses (high granularity)



Results (IV)

 The loss percentile of each portfolio against their exposure volume for banks with market share above 1%



Conclusions & Policy implications (I)

- At aggregate level, our study shows that there is sufficient diversification of the banks' portfolios (due to the netting effects) and the overall RWs are sufficiently prudent.
- We've also shown that in the case of high granularity, the losses are smaller and occur less often.
- However, what is true at aggregate portfolio level is not necessarily true at sector level. Particularly, portfolios made up of exposures towards non-financial corporations experience net losses at percentiles lower than the 99.9 threshold (the losses generated by exposures to some sectors sometimes absorb losses specific to others).

Conclusions & Policy implications (II)

- At macro level, adjustment factors to risk weights seem to be required in the case of exposures towards non-financial companies for some sectors, despite their already higher risk weights
- We considered that there is a need for an increase in the risk weight if the cumulative market share (in that sector) of the banks that simultaneously record losses after the 99.9 percentile exceeds the maxim market share (in that sector) of an individual bank.
- The adjustment factor is computed such as the losses are fully covered by the allocated capital.
- Different for each non-financial corporations portfolio, the multiplying adjustment factor (RW actual 100%):

Agriculture & Commerce

• 1

Real estate

• 1,38

Industry

• 1

Services & Utilities

• 1,52

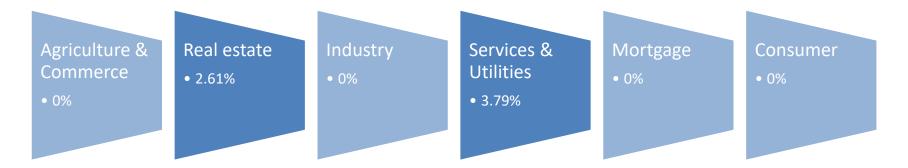
Conclusions & Policy implications (III)

- At micro level, we've estimated the adjustment factors to risk weights that would make the capital (and expected loss allowances) cover the losses in each portfolio for every bank at the 99.9 percentile
- Adjustments for the 17 Romanian banks that have over 1% market share:

		portfolios					
		Agriculture &Commerce	Real estate	Industry	Services & Utilities	Mortage	Consumer
	1	1,00	1,72	1,44	1,40	1,00	1,00
	2	1,51	2,11	1,58	1,53	1,00	1,00
	3	1,00	1,06	1,07	1,45	1,00	1,00
	4	1,15	2,31	1,63	2,45	1,00	1,00
	5	1,28	2,35	2,10	3,48	1,00	1,00
	6	1,00	1,00	1,00	1,00	1,00	1,00
	7	2,68	2,99	6,32	2,59	1,00	1,40
S	8	1,00	1,00	1,00	1,54	1,00	1,00
banks	9	1,25	1,28	1,06	1,45	1,00	1,00
2	10	1,00	1,33	2,37	1,64	1,00	1,00
	11	1,00	1,00	1,00	1,00	1,00	1,00
	12	1,00	1,00	1,08	2,28	1,00	2,06
	13	1,25	1,13	1,67	2,86	1,00	1,35
	14	1,00	1,00	1,00	1,01	1,00	1,00
	15	1,00	1,00	1,00	1,31	1,00	1,00
	16	1,00	1,87	1,27	1,29	1,00	1,00
	17	1,00	4,05	1,00	3,40	1,00	1,41

Conclusions & Policy implications (IV)

- We've also computed a concentration capital buffer, that is the additional capital requirements that would cover the net losses at a 99.9 percentile
- 1. Macroprudential buffer At sector level



2. Microprudential buffer (I) – At bank level for **overall** portfolio (recall slide 14)

Bank (over 1% market share)
• 3.08%

Conclusions & Policy implications (V)

2. Microprudential buffer (II) – At bank level for each sector (recall slide 14)

		portfolios					
		Agriculture &Commerce	Real estate	Industry	Services& Utilities	Mortage	Consumer
	1	0,0%	1,4%	0,2%	0,2%	0,0%	0,0%
	2	0,3%	0,6%	0,7%	0,3%	0,0%	0,0%
	3	0,0%	0,0%	0,1%	0,2%	0,0%	0,0%
	4	0,1%	0,5%	0,3%	0,6%	0,0%	0,0%
	5	0,1%	0,3%	0,4%	0,5%	0,0%	0,0%
	6	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%
	7	2,0%	0,1%	3,1%	0,5%	0,0%	0,1%
S)	8	0,0%	0,0%	0,0%	0,3%	0,0%	0,0%
banks	9	0,5%	0,1%	0,3%	0,4%	0,0%	0,0%
9	10	0,0%	0,4%	1,5%	0,4%	0,0%	0,0%
	11	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%
	12	0,0%	0,0%	0,0%	1,0%	0,0%	0,1%
	13	0,3%	0,2%	0,5%	1,0%	0,0%	0,1%
	14	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%
	15	0,0%	0,0%	0,0%	0,2%	0,0%	0,0%
	16	0,0%	0,6%	0,2%	0,2%	0,0%	0,0%
	17	0,0%	3,2%	0,0%	1,8%	0,0%	0,1%

Disclaimers

- LGD was not modeled, the average coverage for each sector (bank specific)
 was used instead.
- Risk weights represent the volume-weighted RW for each sector and bank.
- The scope was limited to exposures to the real sector (in particular, sovereign exposures were not included).
- The choice of the period used to construct long-term distributions of default rates might affect the final outcome.
- The TTC PDs used for the simulations were obtained following a simple linear calibration. The relative riskiness order among debtors was assumed to remain the same (a single factor is assumed to systematically impact the risk of all debtors).

Future developments

The study shall be extended with:

- Single Name concentration
- Currency concentration
- Geographical concentration

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Thank you!
Any questions?